13.10#14.9#14.10#15.7

December 11, 2017

1 Load MNIST Data

In [1]:
```
# MNIST dataset downloaded from Kaggle :
#https://www.kaggle.com/c/digit-recognizer/data

# Functions to read and show images.

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt



d0 = pd.read_csv('./mnist_train.csv')

print(d0.head(5)) # print first five rows of d0.

# save the labels into a variable l.
l = d0['label']

# Drop the label feature and store the pixel data in d.
d = d0.drop("label",axis=1)
```

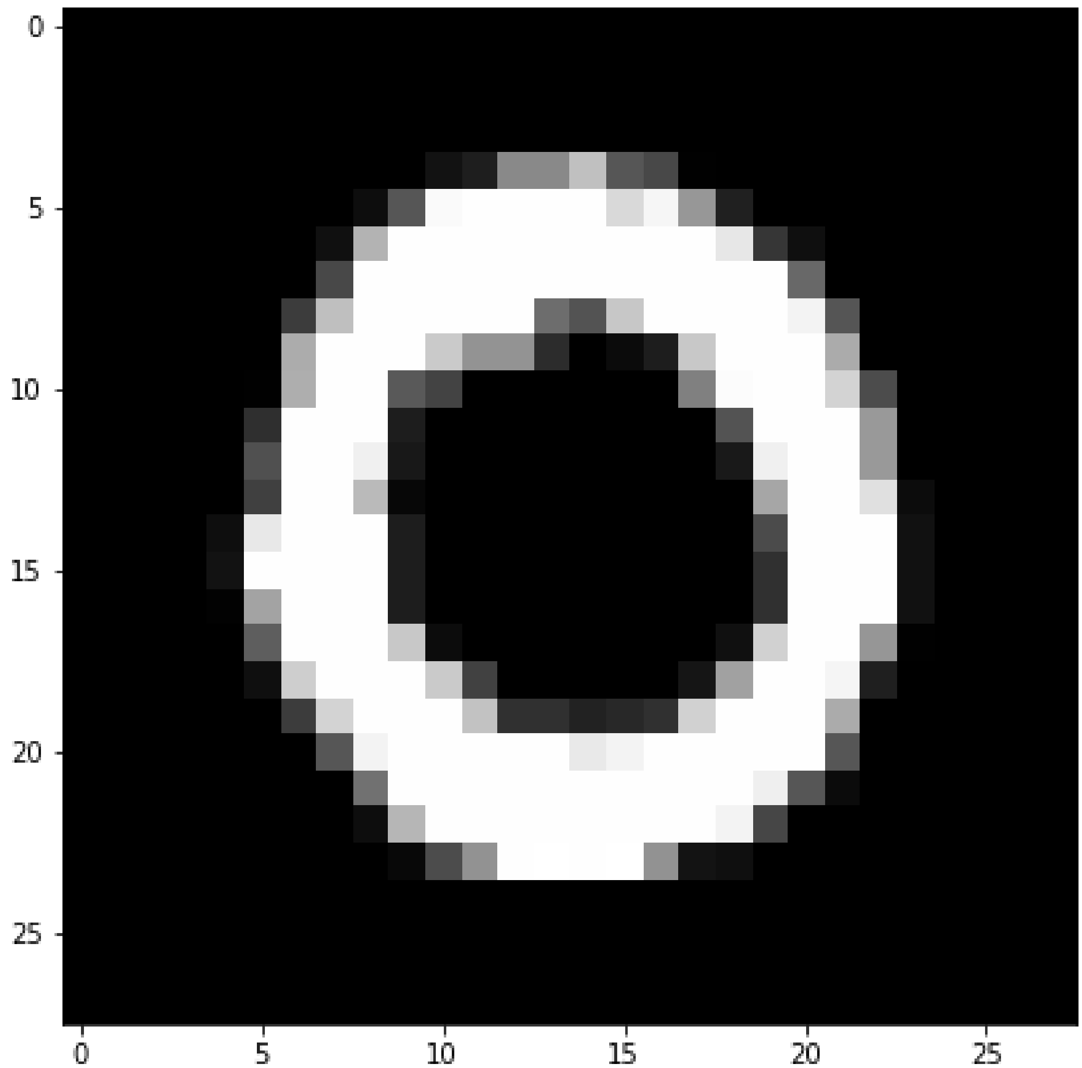
```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8    ...     pixel774  pixel775  pixel776  pixel777  pixel778  \
0       0    ...            0         0         0         0         0
1       0    ...            0         0         0         0         0
2       0    ...            0         0         0         0         0
```

```
3       0    ...             0          0          0          0          0
4       0    ...             0          0          0          0          0

   pixel779  pixel780  pixel781  pixel782  pixel783
0         0         0         0         0         0
1         0         0         0         0         0
2         0         0         0         0         0
3         0         0         0         0         0
4         0         0         0         0         0

[5 rows x 785 columns]
```

In [2]:
```
print(d.shape)
print(l.shape)
```

```
(42000, 784)
(42000,)
```

In [3]:
```
# display or plot a number.
plt.figure(figsize=(7,7))
idx = 1

grid_data = d.iloc[idx].as_matrix().reshape(28,28)  # reshape from 1d to 2d pixel array
plt.imshow(grid_data, interpolation = "none", cmap = "gray")
plt.show()

print(l[idx])
```




```
0
```

2 2D Visualization using PCA

```
In [4]: # Pick first 15K data-points to work on for time-effeciency.
        #Excercise: Perform the same analysis on all of 42K data-points.

        labels = l.head(15000)
        data = d.head(15000)

        print("the shape of sample data = ", data.shape)
```

```
the shape of sample data =  (15000, 784)
```

```
In [7]: # Data-preprocessing: Standardizing the data

        from sklearn.preprocessing import StandardScaler
        standardized_data = StandardScaler().fit_transform(data)
        print(standardized_data.shape)
```

```
(15000, 784)
```

```
In [9]: #find the co-variance matrix which is : A^T * A
        sample_data = standardized_data

        # matrix multiplication using numpy
        covar_matrix = np.matmul(sample_data.T , sample_data)

        print ( "The shape of covariance matrix = ", covar_matrix.shape)
```

```
The shape of covariance matrix =  (784, 784)
```

```
In [10]: # finding the top two eigen-values and corresponding eigen-vectors
         # for projecting onto a 2-Dim space.

         from scipy.linalg import eigh

         # the parameter 'eigvals' is defined (low value to heigh value)
         # eigh function will return the eigen values in asending order
         # this code generates only the top 2 (782 and 783) eigenvalues.
         values, vectors = eigh(covar_matrix, eigvals=(782,783))

         print("Shape of eigen vectors = ",vectors.shape)
         # converting the eigen vectors into (2,d) shape for easyness of further computations
         vectors = vectors.T

         print("Updated shape of eigen vectors = ",vectors.shape)
         # here the vectors[1] represent the eigen vector corresponding 1st principal eigen vect
         # here the vectors[0] represent the eigen vector corresponding 2nd principal eigen vect
```

```
Shape of eigen vectors =  (784, 2)
Updated shape of eigen vectors =  (2, 784)
```

```
In [11]: # projecting the original data sample on the plane
         #formed by two principal eigen vectors by vector-vector multiplication.

         import matplotlib.pyplot as plt
```

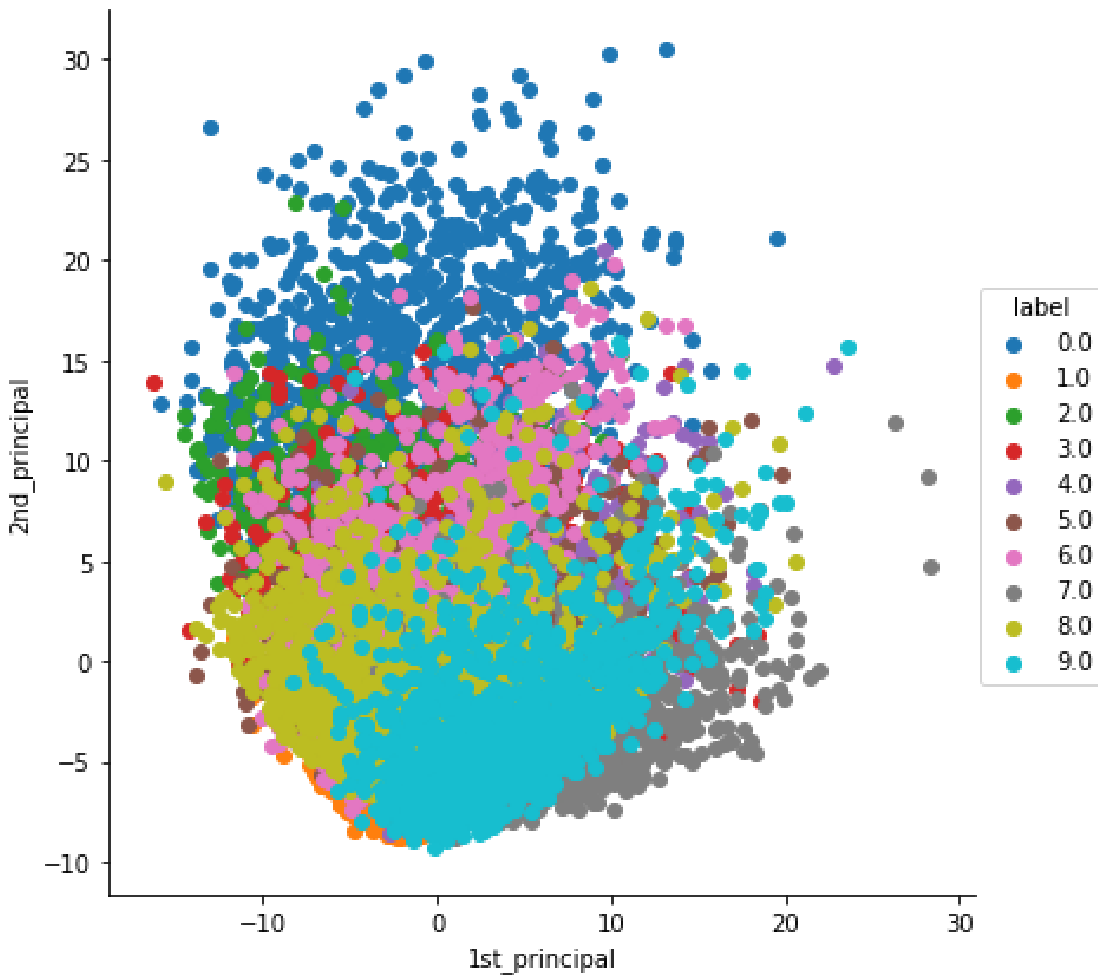
```
new_coordinates = np.matmul(vectors, sample_data.T)

print (" resultanat new data points' shape ", vectors.shape, "X", sample_data.T.shape,"
```

```
 resultanat new data points' shape  (2, 784) X (784, 15000)  =  (2, 15000)
```

In [12]:
```
import pandas as pd

# appending label to the 2d projected data
new_coordinates = np.vstack((new_coordinates, labels)).T

# creating a new data frame for ploting the labeled points.
dataframe = pd.DataFrame(data=new_coordinates, columns=("1st_principal", "2nd_principal
print(dataframe.head())
```

```
   1st_principal  2nd_principal  label
0      -5.558661      -5.043558    1.0
1       6.193635      19.305278    0.0
2      -1.909878      -7.678775    1.0
3       5.525748      -0.464845    4.0
4       6.366527      26.644289    0.0
```

In [13]:
```
# ploting the 2d data points with seaborn
import seaborn as sn
sn.FacetGrid(dataframe, hue="label", size=6).map(plt.scatter, '1st_principal', '2nd_pri
plt.show()
```



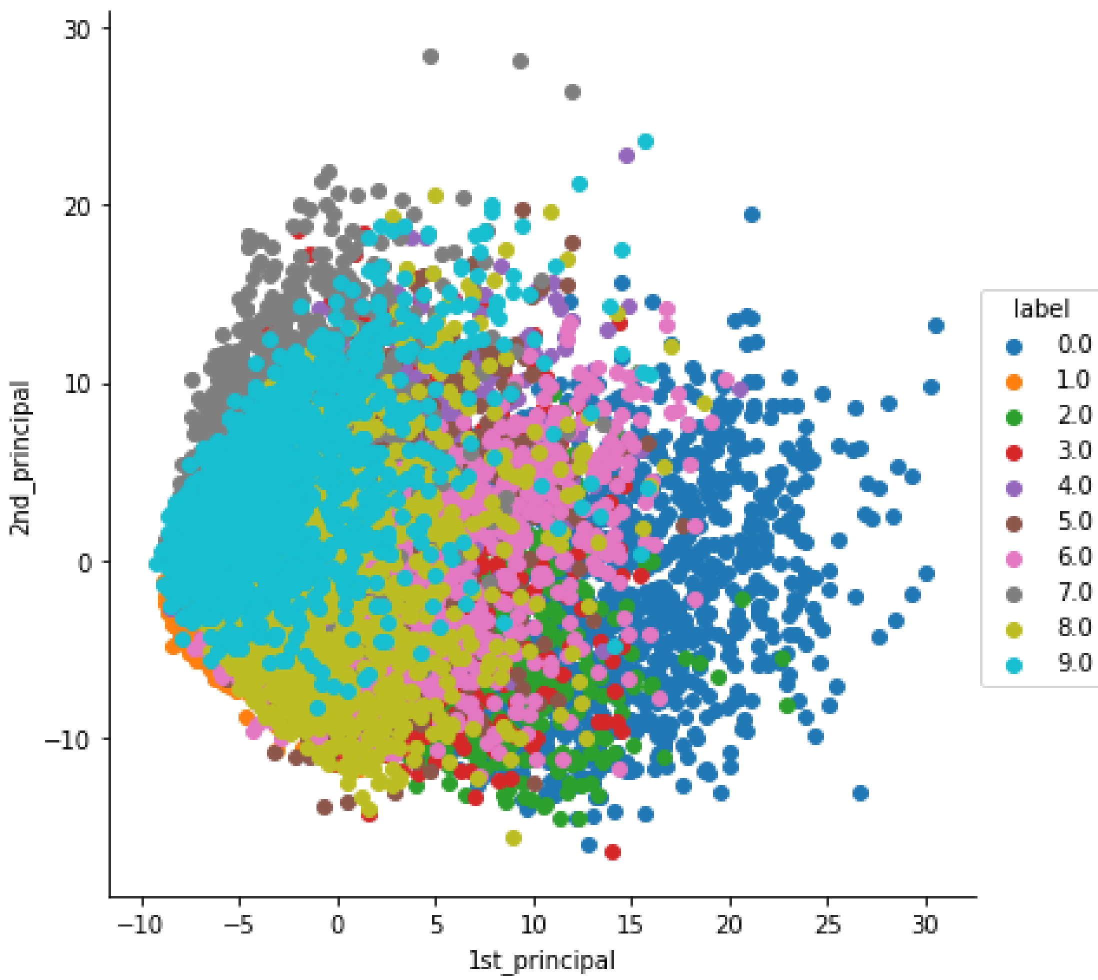
3 PCA using Scikit-Learn

In [14]:
```
# initializing the pca
from sklearn import decomposition
pca = decomposition.PCA()
```

In [15]:
```
# configuring the parameteres
# the number of components = 2
pca.n_components = 2
pca_data = pca.fit_transform(sample_data)

# pca_reduced will contain the 2-d projects of simple data
print("shape of pca_reduced.shape = ", pca_data.shape)
```

```
shape of pca_reduced.shape =  (15000, 2)
```

In [16]:
```
# attaching the label for each 2-d data point
pca_data = np.vstack((pca_data.T, labels)).T

# creating a new data fram which help us in ploting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd_principal", "label"
sn.FacetGrid(pca_df, hue="label", size=6).map(plt.scatter, '1st_principal', '2nd_princi
plt.show()
```

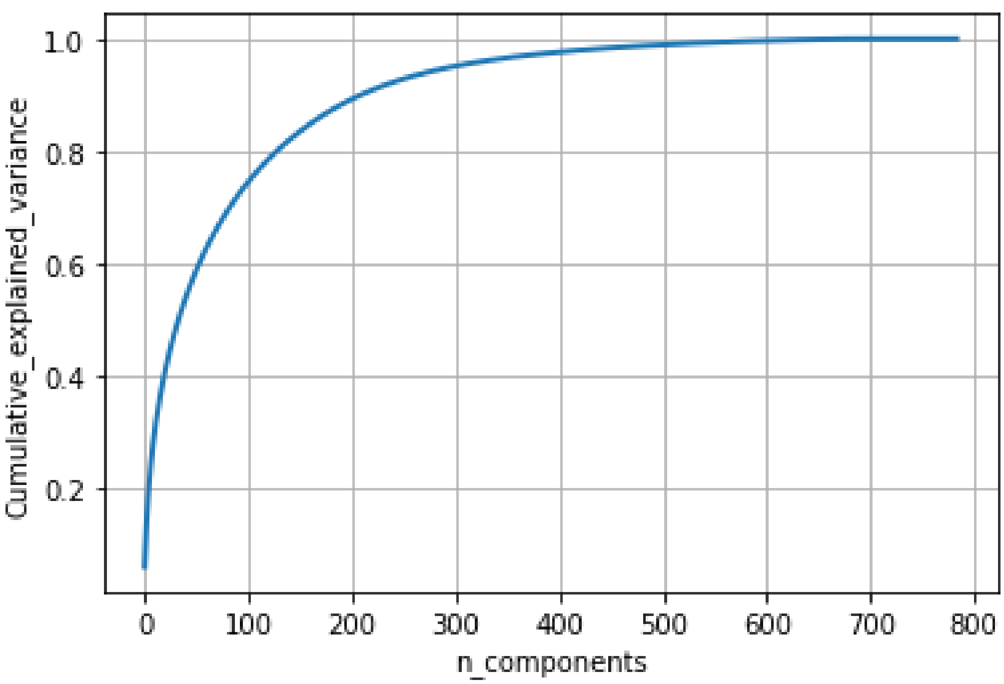


4 PCA for dimensionality redcution (not for visualization)

In [17]:
```
# PCA for dimensionality redcution (non-visualization)


pca.n_components = 784
pca_data = pca.fit_transform(sample_data)

percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_);
```

```
print(percentage_var_explained.shape)
cum_var_explained = np.cumsum(percentage_var_explained)

# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()


# If we take 200-dimensions, approx. 90% of variance is expalined.
```

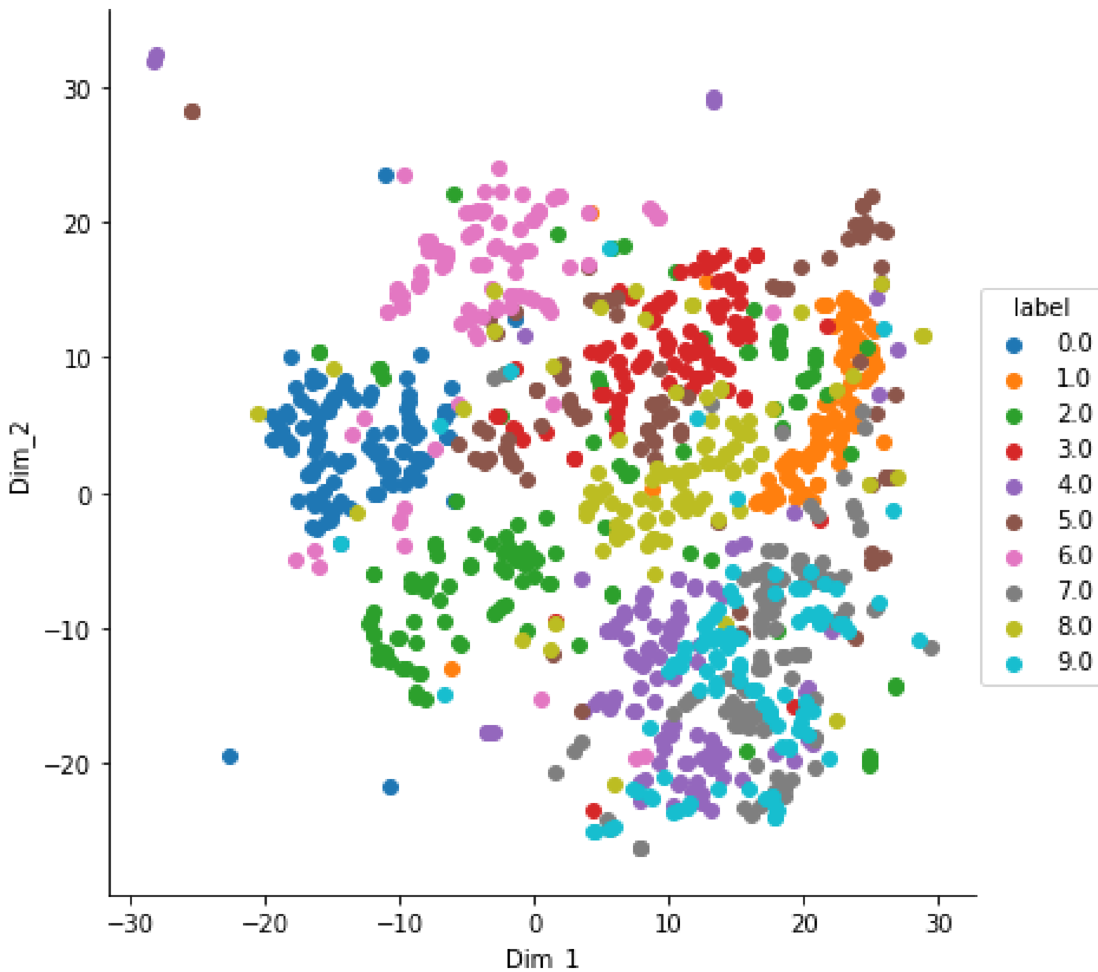
```
(784,)
```



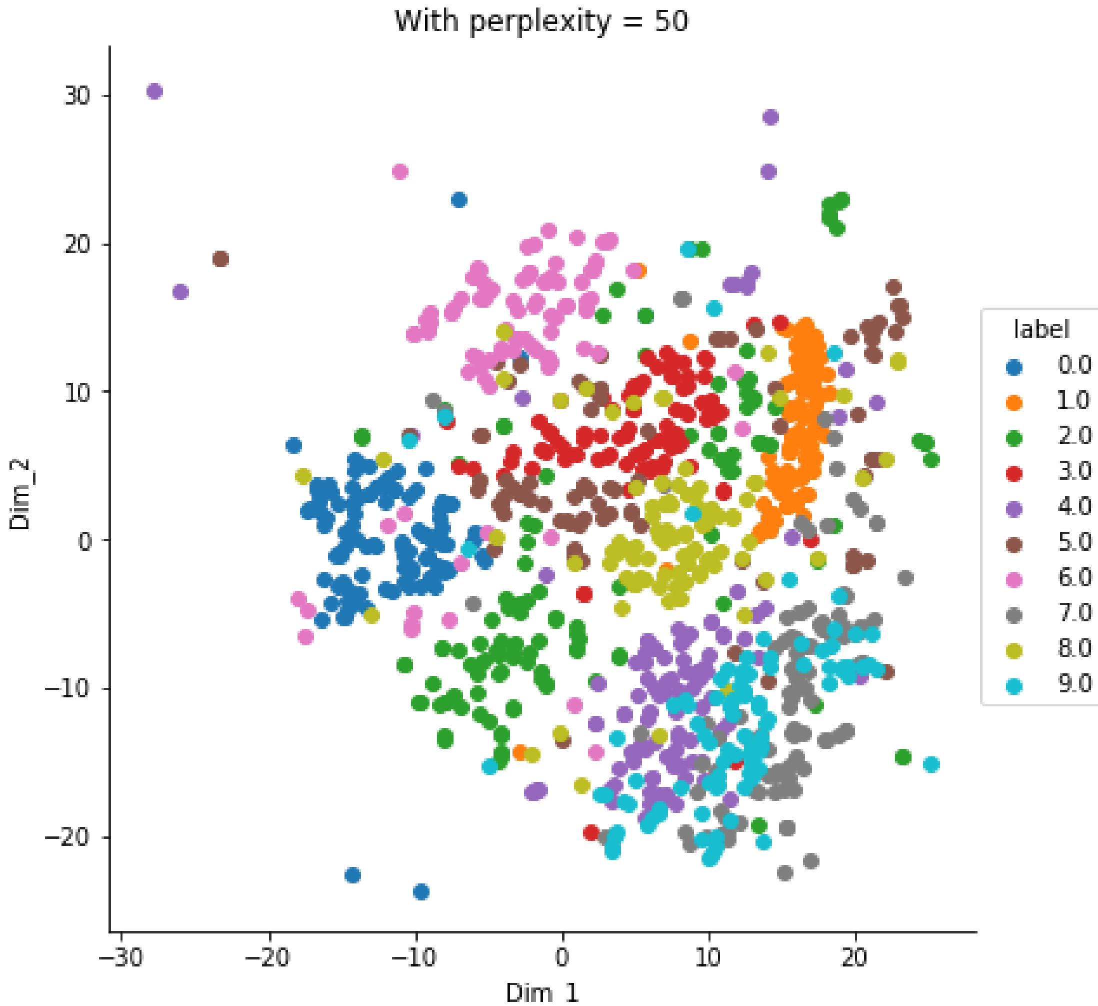
5 t-SNE using Scikit-Learn

```
In [29]: # TSNE
```

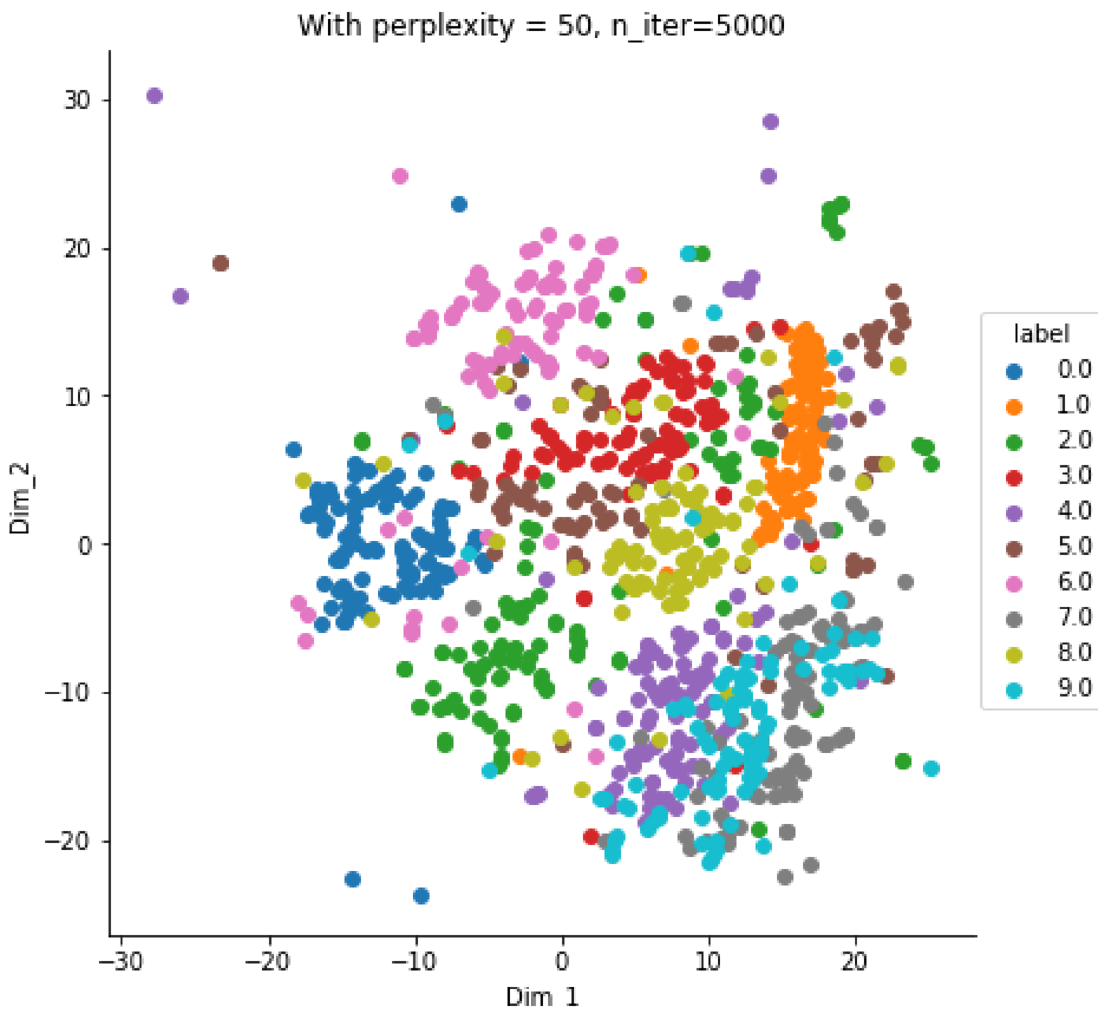
```
from sklearn.manifold import TSNE

# Picking the top 1000 points as TSNE takes a lot of time for 15K points
data_1000 = standardized_data[0:1000,:]
labels_1000 = labels[0:1000]

model = TSNE(n_components=2, random_state=0)
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000

tsne_data = model.fit_transform(data_1000)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legen
plt.show()
```



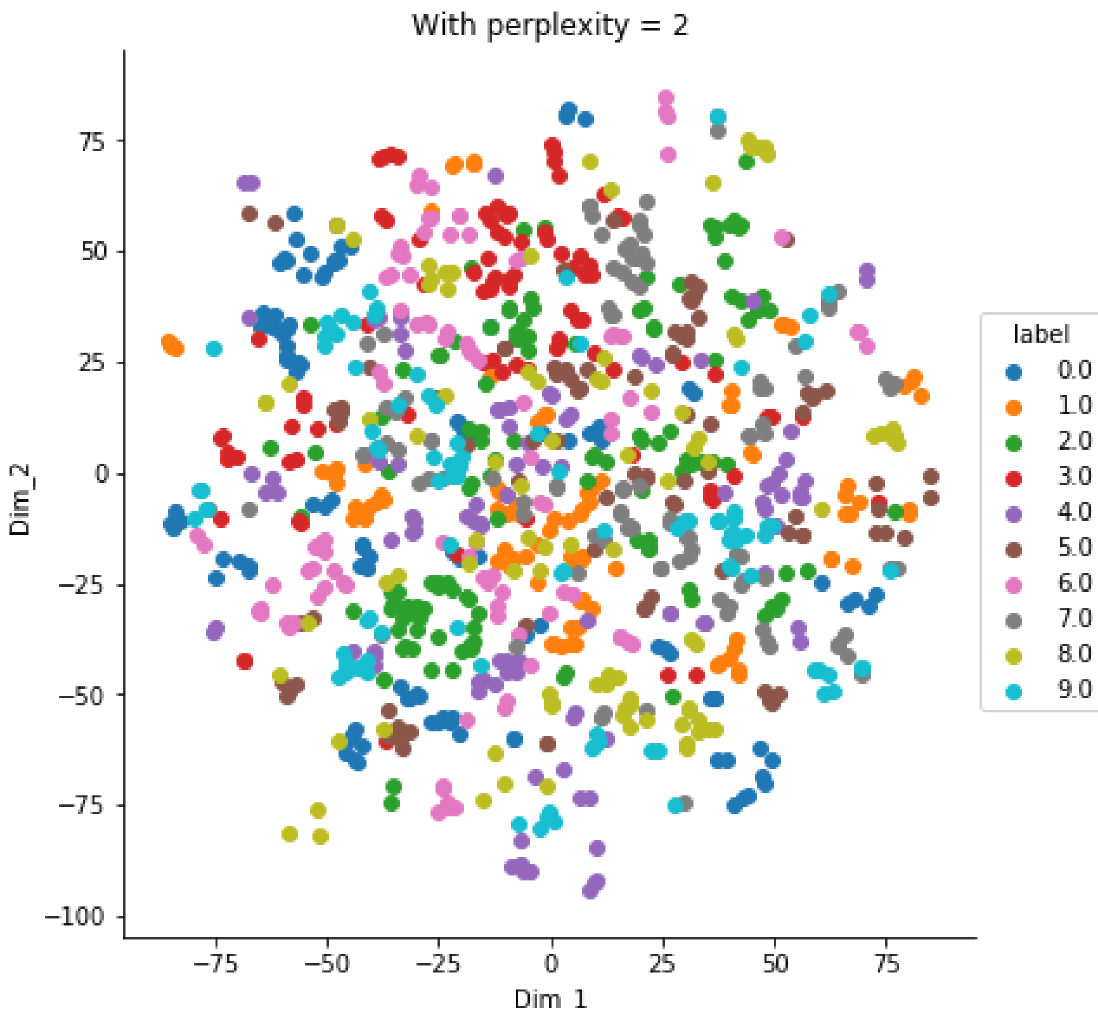
In [21]:
```
model = TSNE(n_components=2, random_state=0, perplexity=50)
tsne_data = model.fit_transform(data_1000)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legen
plt.title('With perplexity = 50')
plt.show()
```




```
In [22]: model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=5000)
         tsne_data = model.fit_transform(data_1000)

         # creating a new data fram which help us in ploting the result data
         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

         # Ploting the result of tsne
         sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legen
         plt.title('With perplexity = 50, n_iter=5000')
         plt.show()
```




```
In [23]: model = TSNE(n_components=2, random_state=0, perplexity=2)
         tsne_data = model.fit_transform(data_1000)

         # creating a new data fram which help us in ploting the result data
         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

         # Ploting the result of tsne
         sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legen
         plt.title('With perplexity = 2')
         plt.show()
```



In [24]:
```
#Excercise: Run the same analysis using 42K points with various
#values of perplexity and iterations.

# If you use all of the points, you can expect plots like this blog below:
# http://colah.github.io/posts/2014-10-Visualizing-MNIST/
```